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Role of Sentiment in Message Propagation: Reply vs. Retweet Behavior in Political Communication

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***Index Terms*— discussions in twitter, information propagation, sentiment analysis**

I. INTRODUCTION

Social media has become an important tool for political communication. For example, politicians make use of Facebook and Twitter for their election campaigns and disseminating political opinions. Such activities can potentially increase engagement of regular citizens as well as politically active users. How uses of social media influence political opinions and opinion changes has become a popular research topic (e.g. see [16]).

Related to information influence, there has been a significant amount of research in modeling information diffusion in the Twitter space. Given a tweet, information propagation can be estimated using several indicators, including a) degree of retweets, b) length of discussions or number of responses generated, c) number of people responded through retweets or reply chains, d) degree of nesting in the reply chains, and e) lifetime of discussion or retweets.

Many researchers make use of 'retweeting' behavior as a mechanism for information diffusion. Some of the work [15, 17] classifies different types of messages based on user characteristics and content features to evaluate retweet rates. Zaman et al. [18] computes the probability of retweets within a timeframe using a collaborative filtering prediction model. Other work [14] associate linguistic styles or sentiment expressions in the message with the degree of retweets. However, there has been limited work on analyzing interactive discussions that are formed through reply-to chains. Unlike retweets, which is often an indication of endorsement, responses to twitter messages can include both positive and negative valence toward the previous message or discussion topics [1]. It also involves more work for the poster since he/she has to generate a new message, which can indicate higher engagement of the participants.

In this paper, we investigate information propagation through discussions and compare how discussion behavior is different from retweet patterns. Building on the existing results on sentiment expressions in social media and information propagation, our work focuses on sentiment or affective factors in information propagation through discussions. We relate sentiment expressions in twitter messages to the degrees of responses generated by the messages. Our hypothesis is that the degree of emotional expressions in the message can affect the degree of responses (through reply-to chains) generated. We compare replies to retweets in terms of how different types of emotional characteristics in the message content affect degree of replies and retweets.

We expect our work can support: a) identifying roles of sentiment in information propagation and b) generating a predictive model of message influence using sentiment information.

II. DISCUSSIONS IN TWITTER

Figure 1 shows an example twitter discussion thread with a sequence of four messages: M1, M2, …, M4 in order. Reply-to relations form trees among messages. The users represent the discussants. User A initiates the thread by expressing his/her sentiment toward election candidates. Others respond to it with further emotional expressions or sympathy. In other political communication within Twitter, discussion threads often form political debates on controversial issues or exchanges of different views.

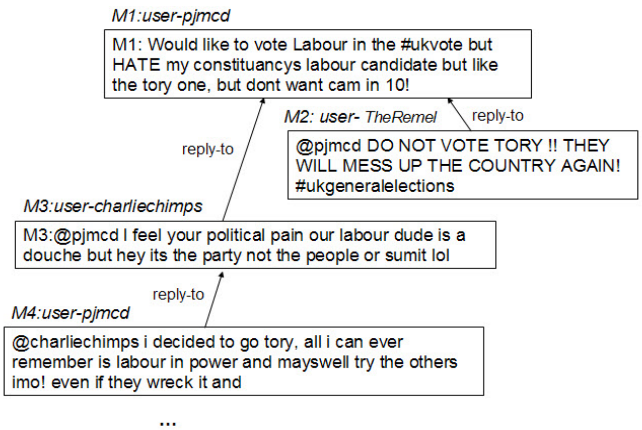

Figure 1. An example discussion thread

III. Supporting Theory and Related Work

There is strong evidence that the expression of emotion by an individual influences how others react. Emotional expressions also evoke complementary and reciprocal emotions in others that help individuals respond to significant social events [5]. Emotions are viewed as primary motivational mechanisms for interpersonal interaction. Rime et al. [12] discuss the possible psychological and social functions of sharing emotions. Emotion plays an important role in social interactions, social comparison, and social influence processes. Heath and Bell [4] have found that rumors are selected and retained in the social environment in part based on their ability to tap emotions.

Sentiment expressions in twitter messages have been analyzed using various content features including emoticons and hashtags as well as frequent words [2]. Kouloumpis et al., [7] analyzed Edinburgh twitter corpus and found that emoticons, hashtags and sentiment lexicons are useful in detecting message sentiment. However, part of speech features were not very useful. Sentiment words and emoticons have been used to classify user types [11] such as influential users use more social words and presents negative emotions. Some others related sentiment word frequencies to public opinion time series including forming of political opinions [8]. Dodds et al. [3] made use of top 50,000 frequent words for message representation and analyzed degree of happiness and its time dynamics.

Our work builds on these results on how emotions affect social responses, and analyzes roles of emotions in message propagation in social medial, focusing on how emotion expressions in online communication affect the degree of responses generated.

Research in sentiment in online discussion forums is relevant to this work. For example, Kim et al. [6] analyzed emotional expressions that arise in online Q&A discussions and relate them to types of discussions, such as resolved vs. unresolved discussions. Qiu et al. [10] analyzes trends of sentiment expressions in cancer forums using a sentiment word list and emoticons. Our work focuses on relating sentiment expressions with degrees of responses generated by the community. We also compare reply and retweet behavior within the same communication context: political election.

IV. Approach

A. Data

TABLE I. UK Political Tweets Analyzed

	Reply-to Chain		
# users	153,440		
# tweets	657,259	N replies=0	N replies>0
# initials	632,993	615,817	171,76
# **replies**	24,266	N/A	N/A
	Retweets		
# users	169,735		
# tweets	777,925	N retweets=0	N retweets>0
# initials	632,993	574,902	58,091
# **retweets**	144,932	N/A	N/A

We used twitter messages on UK political election, posted between Mar/25/2010 and May/11/2010 for around 2 months[1]. Table 1 provides a quantitative summary of the data. "Reply-to" chains are formed based on direct replies between messages, in interactive discussions. Since the data was collected with the given time period, some of the discussion threads do not have the complete information about the message reply-to relations. For example, target messages that a message replies to may be missing. During the thread pre-processing step, we removed the tweets that belong to incomplete threads.

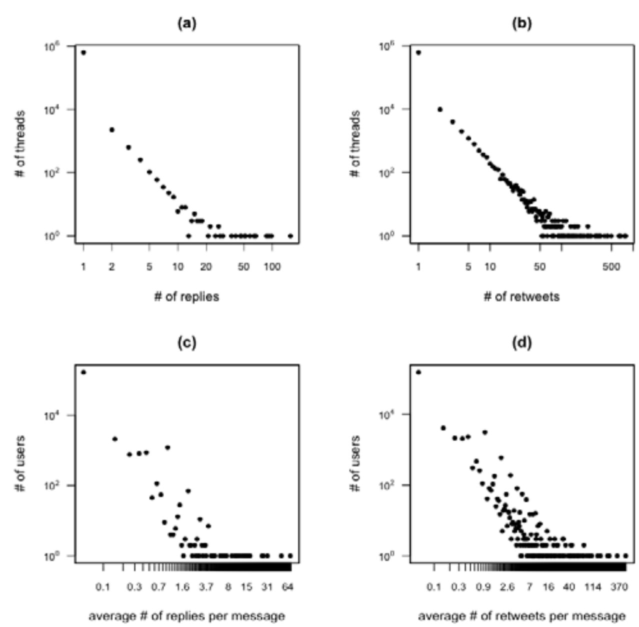

Figure 2. Distributions of Responses per Message and per User

1 The dataset was provided by Matthew Rowe in the Open University.

Figure 2-(a) and (b) illustrates that both the number of replies and the number retweets generated by a message in log-log scale. In both cases, the distributions follow a power law. Many messages generate a few responses or retweets only. We are interested in identifying the differences between popular tweets vs. ones that receive limited responses.

Figure 2-(c) and (d) show distributions of average number of responses and retweets generated per user with his/her messages. Although there are some variances among users, many users receive only a few responses. A small number of popular users exist and numbers of responses that they generate vary a lot. In both per message and per user distributions, retweets and replies present similar distributions: (a) vs. (b) and (c) vs. (d).

B. Sentiment Modeling

Existing studies show that sentiment expressed in twitter messages (tweets) correlate with political views or opinions. Our hypothesis is that sentiment expressions and linguistic features in the initial tweets can affect the number of replies or retweets. That is, the messages containing sentiment words trigger more responses than the ones without them. In order to verify the hypothesis, we examined correlation between the degree of sentiment words and the number of replies or retweets generated.

We characterize sentiment expressions in twitter messages using Linguistic Inquiry and Word Count (LIWC) [9]. There are 64 categories in the English LIWC dictionary, which include approximately 4,500 words or word stems. These words are categorized based on their linguistic or psychological meanings. LIWC is a validated measure that has been used in evaluating emotional and psychological features in diverse corpus of texts including blogs and twitter messages (e.g. see [11]). Building on existing work on twitter sentiment analysis [14], additional content features including positive and negative emoticons, URLs, hashtags and punctuation marks were included. The list of variables used in the analysis is listed in Table 2.

The 4th and 5th columns of Table 2 show user-based statistics: mean and standard deviation of all the users. They show that there is a large variance in the number of followers and account age. Among content features, use of complex words and sentiment expressions vary more than others. Generally there are more retweets than replies per user and the degree of retweets generated varies more than the degree of replies. The 6th and 7th columns show characteristics of twitter messages. The per messages statistics show a similar pattern, including the degrees of sentiment expressions and content features.

Table 3 lists statistics for top 5 most replied and retweeted accounts. Although two users overlap between the two, most retweeted accounts don't necessarily receive more replies. For example, user accounts like SkyNewsBreak have smaller affect values than other users, and receives fewer replies. When we compare these values with the statistics of all the users shown in Table 2, the degree of affective expressions seem relatively higher than other regular users.

TABLE II. VARIABLES USED FOF ANALYSIS

Category	Variable	Description	Statistics per user		Statistics per message	
			Mean	Std. Deviation	Mean	Std. Deviation
Twitter	Ntweets	The number of tweets	4.28	39.69	N/A	N/A
	Nreplied	The number of replies received	0.16	2.29	0.04	0.45
	Nretweeted	The number of retweets received	0.94	16.81	0.23	3.26
User	Nfollowers	The number of followers	860.79	26541.66	N/A	N/A
	Account Age	Number of days since joined	353.24	239.78	N/A	N/A
LIWC Linguistic	WC	Word count	16.41	5.57	17.37	7.84
	Sixltr (%)	Words>6 letters	19.39	10.73	21.17	12.11
	Pro1 (%)	1st personal pronouns (I, we, mine)	2.74	4.06	2.12	4.04
	Pro2 (%)	2nd personal pronouns (You, your)	0.76	2.05	0.68	2.36
	Pro3 (%)	3rd personal pronouns (she, her, him)	0.90	1.82	0.97	2.50
LIWC Affect	Affect (%)	Positive or negative emotions	5.90	6.05	5.52	6.35
	Posemo (%)	Positive emotion (Love, nice, sweet)	3.39	5.10	3.53	5.20
	Negemo (%)	Negative emotion (Hurt, ugly, nasty)	1.98	3.56	1.96	3.96
Additional content features	Mention	Existence of mention	0.30	0.63	0.11	0.31
	Hashtag	Existence of hashtags	0.56	0.81	0.41	0.49
	URL	Existence of URLs	0.55	0.82	0.32	0.46
	Posemoticons	Existence of positive emoticons	0.05	0.19	0.02	0.14
	Negemoticons	Existence of negative emoticons	0.01	0.10	0.01	0.07
	Qmark	Existence of ?	0.21	0.36	0.17	0.37
	Exclamation	Existence of !	0.26	0.37	0.24	0.42

TABLE III. TOP MOST TWEETED AND REPLIED USER ACCOUNTS

Variable \ Popular Accounts	Top 5 replied users					Top 5 retweeted users				
	REP U1	REP U2	REP U3	REP U4	REP U5	RET U1	RET U2	RET U3	RET U4	RET U5
Ntweets	11	112	2	334	66	72	27	11	112	70
Nreplied	374	297	254	222	222	76	54	374	297	23
Nretweeted	1685	1495	432	804	666	2973	2015	1685	1495	1196
Nfollowers	3083517	36405	133261	8665	43391	5962	78614	3083517	36405	47556
Account Age	407.82	454.20	462.00	413.39	453.17	251.86	1057.85	407.82	454.20	176.57
WC	18.73	18.39	24.00	18.28	17.53	18.81	20.70	18.73	18.39	16.27
Sixltr (%)	18.05	22.55	18.52	22.04	20.21	18.03	15.70	18.05	22.55	22.08
Pro1 (%)	2.91	2.87	4.76	3.29	1.13	0.71	2.86	2.91	2.87	0.08
Pro2 (%)	1.39	0.98	3.71	0.62	0.20	1.50	0.58	1.39	0.98	0.00
Pro3 (%)	1.18	1.27	1.85	1.04	1.06	1.34	1.21	1.18	1.27	0.94
Affect (%)	8.79	5.88	7.94	6.40	8.19	8.23	7.29	8.79	5.88	4.21
Posemo (%)	8.79	4.83	0.00	4.78	6.74	5.18	3.79	8.79	4.83	2.58
Negemo (%)	0.00	1.05	7.94	1.62	1.38	3.05	3.35	0.00	1.05	1.64
Mention	0.00	0.80	0.00	0.57	0.06	0.03	0.22	0.00	0.80	0.00
Hashtag	0.00	1.29	0.00	0.72	0.03	1.14	0.44	0.00	1.29	0.03
URL	1.64	0.95	0.00	0.54	0.52	0.36	0.67	1.64	0.95	0.11
Qmark	0.18	0.37	0.50	0.21	0.08	0.04	0.07	0.18	0.37	0.00
Exclamation	0.36	0.31	0.00	0.28	0.24	0.19	0.37	0.36	0.31	0.03
Pos. Emoticons	0.00	0.00	0.00	0.77	0.00	0.00	0.07	0.00	0.00	0.00
Neg. Emoticons	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
User Name	REP: U1 - **eddieizzard**, U2 - **johnprescott**, U3 - alandavies1, U4 - BevaniteEllie, U5 - campbellclaret RET: U1 - UKLabourParty, U2 - bengoldacre, U3 - **eddieizzard**, U4 - **johnprescott**, U5 - SkyNewsBreak									

C. Regression Analysis

We performed a regression analysis on which of these affective variables explain the number of replies or retweets generated from the message. The following equation represents the model:

$$log\,(y_i) = \beta_0 + \beta_1 x_{1,i} + \beta_2 x_{2,i} + \ldots + \beta_M x_{m,i}$$

where y_i represents expected number of replies or retweets as dependent variables. X_{ij} means each of the other variables listed in table 2, including LIWC affect values and additional content features.

We perform both per user and per message analysis. That is, we relate the content features to these: a) Message perspective: degrees of replies and retweets generated by the initial message in the thread; b) User perspective: average degrees of replies and retweets generated by the user's messages.

V. RESULTS

This section presents the results from a regression analysis, described above. Table 4 summarizes the result. The numbers marked with stars indicate significant variables.

A. Role of Sentiment in Message Propagation

The regression analysis reveals that sentiment variables and some of the content features are significantly related to number of replies and retweets generated. In particular, both the numbers of replies and retweets are positively correlated with existence of negative sentiment words and negatively correlated with positive words. Different types of negative emotions (anger vs. anxiety) seem to affect retweets and responses in different degrees, and we plan to investigate further details on their roles. Although the coefficient values are small, account age and number of followers are positively correlated with the degrees of responses and retweets.

B. Differences between reply vs. retweet behavior

Other content features expose the differences between retweet and reply behaviors; emoticons affect retweets but not replies. URLs, mentions and hashtags are significant factors but their effects are opposite: for example, messages with URLs are retweeted often but generate fewer replies. This may be due to the fact that messages with URLs may contain factual information or reports rather than expressions of opinions that can generate responses. Also first person pronouns such as "I" and "we" generate more replies but reduces retweets. Statements on personal matters seem to promote more replies from the Twitter audience.

C. Message perspective vs. user perspective

Generally 'User Perspective' results share similar significant variables for the number of replies and retweets generated: pronouns, mentions, hashtags, URLs, and many sentiment features are correlated with the degrees of responses. However, there are a few variables that present differences. For example, positive emotion words are positively correlated with retweets. Note that as shown in Table 2, there is a high variance (Std. dev. > 16) in the number of retweets that users' messages generate. We conjecture that variances in messages posted by the same user, including variances in the sentiment and content features, may contribute to these differences, but further analysis of such within-user variances are needed. For example, we can profile users based on such sentiment variances, and analyze them according to their degrees of variances.

TABLE IV. SENTIMENT VARIABLES AND REGRESSION ANALYSIS RESULTS

	Model		Message Perspective		User Perspective	
	Dependent / Independent		log (Nreplied)	log (Nretweeted)	log (avg. Nreplied)	log (avg. Nretweeted)
User	Account Age		0.001***	0.001***	0.001***	0.001***
	Nfollowers		2.78E-06***	2.55E-06***	2.50E-06***	1.63E-06***
LIWC Linguistic	Pronouns	1st	0.205***	-0.054***	0.041***	-0.011***
		2nd	0.199***	0.284***	0.066***	0.074***
		3rd	0.074***	0.058***	0.005	0.019***
	Swear		-0.017***	-0.041***	-0.029	-0.048***
LIWC Affective	Posemo		-0.035*	-0.019**	-0.018***	0.025***
	Negemo	Anxiety	0.189***	0.042***	0.006***	0.037***
		Anger	0.073***	0.153***	0.086	0.025***
		Sadness	-0.038**	-0.010	0.012	-0.047***
LIWC Cognitive	Causation		0.002	-0.001	0.007	-0.016***
	Tentative		0.114***	-0.020***	0.050***	-0.019***
	Certainty		0.086***	0.102***	0.003	0.02***
	Inhibition		-0.090***	-0.042***	0.026	-0.006
Additional content features	Mention		0.241***	-0.318***	0.076***	-0.411***
	Hashtag		-0.154***	0.233***	-0.178***	0.262***
	URL		-0.671***	0.080***	-0.537***	0.053***
	Pos. Emoticons		-0.065	-0.339***	-0.406***	-1.033***
	Neg. Emoticons		0.131	-1.064***	-0.437**	-1.217***
	Qmark		-0.912	-0.230***	0.209***	0.011
	Exclamation		0.154***	0.132***	0.051	-0.068**
Note that *p<0.05; **p<0.01; ***p < 0.001.						

VI. SUMMARY AND DISCUSSION

We confirmed our hypothesis that the degree of emotion expressions in twitter messages can affect the number of replies generated as well as retweet rates. However, due to the difference in the nature of endorsement (retweet) vs. responses (replies or conversation), some of the variables present opposite roles in explaining the degree of responses they receive. Some of the differences between user-based analysis vs. message-based analysis need further investigation based on individual differences.

We are currently extending the current sentiment analysis work by adopting the speech act framework [13]. The extended model explicitly represents differences between various sentiment information including agreement/disagreement and targets of the sentiment. The model will capture sentiment dynamics in message exchanges and how different types of interactions promote longer discussions. The model will also support sentiment-based user profiling by clustering users based on sentiment similarities.

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